Automatic Control and System Engineering Journal, ISSN 1687-4811, Volume 17, Issue 2, ICGST, Delaware, USA, December 2017

www.icgst.com

Multi-Sensor Fusion Indoor Security Based on Interval Probability, Extended Kalman Filter and Fuzzy Rules Pruning

Ali Alqudaihi, Mohamed Zohdy Ph.D. Hoda Abdel-Aty-Zohdy Ph.D.
Department of Electrical and Computer Engineering, Oakland University, Rochester, MI, USA
aaalquda@oakland.edu, zohdyma@oakland.ed, zohdyhsa@oakland.edu

Abstract
In this paper, noisy heterogeneous multi-sensors, namely Infrared, Active Sonar and Pressure sensors are used for indoor security monitoring. A new approach of enhancing the measurement estimation applying an interval probability to the Extended Kalman Filter process and measurement covariances. A total of four different combinations of the covariances were examined by the addition of upper and lower distributions bounds which helped to find the finest combination that keeps the covariance matrices symmetric and positive definite. In addition, Fuzzy-Logic I rules pruning methods and their applications in security monitoring systems and decision-making rules are addressed and discussed.

Keywords: *Multi-Sensor Data Fusion, Interval Probability, Upper/Lower Probability Distribution, Extended Kalman Filter, Measurements Fusion, State Vector Fusion, Fuzzy-Logic I, Rule Pruning.*

Nomenclature

DF	Data Fusion
PR	Pressure Sensor
AS	Active Sonar
IR	Infrared Sensor
EKF	Extended Kalman Filter
IP	Interval Probability
PUB	Probability Upper-Bound
PLB	Probability Lower-Bound
FL I	Fuzzy Logic I
SD	Suspiciousness Degree

1. Introduction
Security monitoring systems has been a hot topic for a long time. The aid of utilizing multi-sensory data systems has led to a more reliable tracking and estimation results; which wouldn't be possible if a single sensor's technique is applied especially if users/consumers main concern is accuracy and measurements reliability. In the area of monitoring valuable assets, many areas increased the security devices demand since the ways of breaking-ins has developed as well. Robustness of the system can be enhanced by fusing multiple sensory data which will make the system less susceptible against the interference that may cause untrustworthy measurements.
The Kalman filter (KF) has found wide application in different controllable systems for identification purposes. The principle theory utilized in these types of filters is the Markov Model that assumes that there exist linear dependencies between systems and Gaussian noise [8].
The importance of multisensory fusion applications has necessitated for increased research about it [2]. As sensory organs are to human, sensors are to systems. They collect information about the system's environment [1] Multisensor fusion involves combining data received from sensors. It could be a single sensor taking data of various parameters or multiple sensors within the multisensor fusion system. The information often obtained is much better and satisfactory than that obtained if the sensors are left to operate independently.
The paper organization is as follows: Section (2) surveys the research's related works and what have been done to the associated case studies. Section (3) reviews the problem motivation and formulation. Sensor Fusion definition, applications, levels, and limitations are discussed in Section (4). Section (5) introduces the Extended Kalman Filter equations and its ongoing cycle. Section (6) provides the theory of interval probability while Section (7) explains how the EKF states and measurements errors are quantified applying the IP. Section (8) discusses the rules pruning methods and how it can reduce Fuzzy Logic I number of rules. Finally, Sections (9), (10) and (11) shows the results of the presented approaches, a conclusion and a reference of sources used in the research consequently.

2. Related Work Survey
Different scholars have in the past utilized the probability intervals in the to extend the Kalman filtering mechanism. Zohdy, Khan and Benedict [12] attempt to explain the use of interval probability in the Kalman filtering mechanism by conducting a Kalman estimation of two filters with diverse gains K1, noise covariance Q and a constant KQ. For the first instance, a noise covariance of Q=10 is applied to a Kalman filter having an associated gain of K1=1 to provide a

constant kQ = 10. A second filter utilizes similar parameters as the first but the filter gain is changed. The variation in the filter parameters of the first and second Kalman filters in this example average at 0.08 with the high confidence level being indicated by 0.15 and the low confidence level being indicated by 0.04 [12]. Zohdy, Khan and Benedict's explanations could be utilized in the exploration how the interval probability could be applied to measurement error covariance, and system error covariance as the high support (the alignment of poor measurements) has the capability of lowering the gains for the proceeding iterations after moving the estimator further from the actual state. Consequently, the error would be magnified.
Another work by Hu, Want, Cheng and Zhong is considering the GIP to be applied to system errors and measurement errors. Their method is to differentiate between the state errors and observation errors with random by estimating the bounds of both errors where the EKF can find which error values between those bounds to be chosen [8]. Their proposed method can fine tune the EKF better with GIP compared to the classical EKF.

3. Motivation and Problem Formulation

The security monitoring system with an innovative Fuzzified Extended Kalman Filter and Fuzzy Logic I for decision making is explained thoroughly in a separate research project [1st paper]. The major objective of the system is to track moving agents with three heterogenous sensors namely: Active Sonar (AS), Infrared (IR), and Pressure Sensitive Floor (PR) sensors. Once the moving agents' tracks are monitored, the security system detect and recognize their intentions toward any valuable/monitored asset in the area under surveillance. The sensors measurements, which are heterogeneous as they provide independent measurement types and homogenous as each moving agent is tracked with three of the same type of sensors, data are filtered and fused to obtain the most accurate distance from those assets and the corresponding weights of each agent. The sensors data are independent and don't communicate with each other; however, the fusion techniques are used to mix their outputs and filter them to minimize any disturbance noises from both the system and the sensors. This research is focusing on applying interval probability theory to modify and enhance the covariances of sensor outputs and states. The results of the improved covariances are compared to the hyper-fuzzified EKF method that was applied in [1st paper]. Moreover, the moving agents' different interaction possibilities are studied and compared which can help to understand how the system can identify how multiple agents communicate with each other. Lastly, rule pruning techniques are manipulated to reduce and/or eliminate any low weight, redundant or unused rules in the decision-making process that utilize Fuzzy Logic I.

4. Sensor Fusion

Sensor Fusion refers to the combination of data drawn from physical sensory data and transforms it to a better form that would enable the use of these sources individually. It could be a single sensor taking data of various parameters or multiple sensors within the multisensor fusion system. Sensor fusion blocks transform received data from the source to a representation that can be fed into the control application thus finishing the process of multisensor integration [2].
The multisensory system has a permanent database that keeps all data thus keeps the system functioning as usual even when there is a partial failure. The data received from each sensor compliments each other therefore limiting the margins of error in interpretation by the controlling application. A multisensory fusion system employs optical and ultrasonic sensors, which means the information data cannot be altered.
The system provides accurate and confirmed measurements. This increase the confidence of the system. When a sensor takes one measurement, it is confirmed by all other sensors working in a similar domain. Also, the accuracy (resolution) is improved because of fusion of the many independent properties results to a better value as compared to the measurement made by a single sensor.
A further benefit of sensor fusion technology is that it helps in reduction of complexity of a system. This is because it can handle a huge amount of data streams that may be ambiguous, imprecise or even incomplete.
Multisensory fusion systems are gaining fame because of their advantages. The system can be reliable since the characteristic intrinsic redundancy can help the system function even in the case of partial failure. The data received from each sensor compliments each other therefore limiting the margins of error in interpretation by the controlling application.
Multisensor Fusion has many applications. Its integration has been useful majorly in security systems. It involves multilevel surveillance and multi-detection systems. Multilevel surveillance structures include active detection modules, passive detection modules, image systems, supervised computers and intelligent homes. It includes motion detectors such as passive infrared, microwave, ultrasonic sensors and vibration sensors and particular types of cameras for images [1]. Security monitoring systems also use databases, human input, and the priori information.
Data is first collected by the security monitoring system and loaded for the fusion process then the data is refined in the object refining process to make it easily identifiable. The refined data is then assessed by analyzing various data collected in the first process to reduce its vulnerability and then stored in a database. Process refinement monitors real-time constraints and can relocate sensors and sources to complete a given task. Finally, results are relayed to the user in the form of light or sound.
In robotics, it increases flexibility and productivity by doing various operations in the industry such as handling of materials, assembly, inspection, and fabrication. It is also

used in military applications such as intelligence collection and analysis, assessment, defense mechanisms et cetera [1]. Multisensor fusion is helpful in remote sensing in the fields of Agriculture, weather forecasting, and climate. Transportation systems such as intelligent cars and other advanced biomedical applications use multisensory fusion [2].

A. Levels of Multisensor Fusion

1. Security monitoring systems are a major application of multisensor fusion. It involves multilevel surveillance and multi-detection systems. Multilevel surveillance structures include active detection modules, passive detection modules, image systems, supervised computers and intelligent homes. It includes motion detectors such as passive infrared, microwave, ultrasonic sensors and vibration sensors and particular types of cameras for images. Security monitoring systems also use databases, human input, and the priori information. This data then goes through the following process:
2. In source preprocessing, also termed as subject-object assessment, data collected by the security monitoring system is allocated to various processes. The main aim of this is to lower the load for the fusion process.
3. Object refinement (object assessment process): It is also labeled as level (1). This stage involves object alignment; changed into similar units and based on a common reference frame by employing the various data classification techniques. It makes the data easily identifiable. For instance, it will enable the security monitoring system to identify a moving object as either a person or animal.
4. Situation refinement (assessment): It involves analyzing the various classes of data from level (1). It then relates the objects to observed events to establish their correlation. Often labeled as level (2)
5. Threat refinement: This is also termed as impact assessment. The security monitoring system uses priori information and predictions to deduce vulnerabilities and when to execute an operation. It also involves database management. Often labeled as level (3)
6. Process refinement: It monitors real-time constraints and can relocate sensors and sources to make a given task complete.
7. The final process is relaying the results to users. It can be in the form of a signal (sound, light, etc.)

B. Sensor Fusion Limitations

Limited coverage regarding space. Normally, one sensor can only cover a defined region. Given the example of temperature recording of water in a boiler, the estimated temperature does not portray that of the boiler. Only the water.

Limits measurements. Some sensors require a specific set up time to work and convey measurements [3]. This limits the maximum number of measurements that can be taken. In this case, most measurements are gotten from individual sensors thus resulting to imprecision as earlier discussed.

5. Extended Kalman Filter

Extended Kalman Filter (EKF) is a nonlinear form of the well-known KF that was founded by and named after Rudolf Kalman in 1960. The EKF is a recursive estimation algorithm consist of two iterative phases which are the Update/Prediction phase and the Estimation/Correction phase. The filter only needs the most recent measurements to predict or estimate the following state of the system which makes EKF works faster than the other state estimators.

For a discrete nonlinear stochastic difference equation, the model can be formulated as Equations (1) and (2):

$$\tilde{x}_k = f(\hat{x}_{k-1}, u_{k-1}) + w_{k-1} \quad (1)$$

$$\tilde{y}_k = h(\tilde{x}_{k-1}) + v_{k-1} \quad (2)$$

Where:

x	system state vector
f	nonlinear system's dynamics
u	control vector
w	system's process noise
y	observation equation
h	measurement function
v	measurement's error covariance

w_{k-1} and v_{k-1} , from Equations (1) and (2), are assumed to be system noise and measurement noise respectively where they are white Gaussian with zero mean.

Figure (1) lists all the equations of the EKF and show the ongoing cycle of prediction and corrections phases.

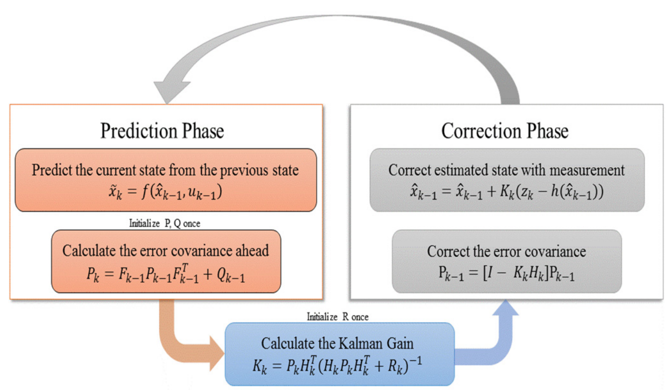

Figure. 1: EKF ongoing cycle and equations

The EKF needs to calculate the Jacobian's matrix, partial derivatives, of the state vector nonlinear elements F in the prediction phase with respect to the states and the Jacobian's matrix of measurements equation elements H in the correction phase with respect to the states again as stated in Equations (3, 4, 5 and 6) correspondingly:

$$F_k = \nabla f_k \,|\hat{x}_k \quad (3)$$

$$\nabla f_k = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_n}{\partial x_1} & \cdots & \frac{\partial f_b}{\partial x_n} \end{bmatrix} \tag{4}$$

$$H_k = \nabla h_k \,|\hat{x}_k \tag{5}$$

$$\nabla h_k = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \cdots & \frac{\partial h_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial h_n}{\partial x_1} & \cdots & \frac{\partial h_b}{\partial x_n} \end{bmatrix} \tag{6}$$

6. Interval Probability

Interval probability is a crucial concept utilized in the evaluation of uncertainty [9]. The theory of interval probability bases on a collection of three primary axioms and provides a common ground for the evaluation of the various aspects of uncertainty [10]. Interval probability, also known as the imprecise probability is primarily applied in mechanical systems having conflicting, vague or scarce information regarding probability distribution [11]. The key goal of this research paper is to analyze the extended Kalman filter based on interval probability and the application of the imprecise probability to measurement error covariance and system error covariance.

The Kalman filter is a typical illustration of the applicability of the interval probability. Different scholars have in the past utilized the probability intervals in the to extend the Kalman filtering mechanism.

Robustness plays a crucial role in the Kalman filtering mechanism. The a priori and a posteriori error covariance matrices, $P_{k|k-1}$ and $P_{k|k}$ consequently, of the filter must be kept positive definite and symmetric for it to work excellently [7]. However, round off errors might lead to the violations of the two conditions. Therefore, the loss of symmetry must be dealt with to ensure the achievement of positive definite. The primary causes of non-positive definite might be the measurement update or the time-update equations of the filter [7].

$$P_k = F_{k-1} P_{k-1} F_{k-1}^T + Q_{k-1} \tag{7}$$

Equation (7) is considered as the addition of the quantities that are both positive-definite result in a positive definite. The second equation (Equation 8) to be considered is that the error covariance matrix of the measurement update:

$$\mathrm{P}_{k-1} = [I - K_k H_k]\mathrm{P}_{k-1} \tag{8}$$

The equation yields a positive definite with several round off errors due to the subtraction operation.

7. Error Quantification

Bounds play a crucial role in error quantification. An interval probability that combines general intervals and aspects of probability is used in an extended Kalman filter to quantify irreducible and reducible quantities simultaneously. The inclusion of distributions between interval probability upper and lower bounds (Equation 9) assist in quantifying systemic errors in Kalman filters thereby assisting designers to eliminate errors [11].

$$([\underline{x}; \bar{x}]): \underline{x}, \bar{x} \in \mathbb{R} \tag{9}$$

The proposed method in this paper is to find the maximum and minimum Probability Interval of the system noise error covariance Q and the measurement noise error covariance R. Both Q and R upper and lower bounds (Equations 10 and 11) represents the highest and lowest interval that can be reached without causing EKF estimations to converge.

$$\left([\underline{Q}; \bar{Q}]\right): \underline{Q}, \bar{Q} \in \mathbb{R}, \underline{Q} \geq 0, \bar{Q} \geq 0 \tag{10}$$

$$([\underline{R}; \bar{R}]): \underline{R}, \bar{R} \in \mathbb{R}, \underline{R} \geq 0, \bar{R} \geq 0 \tag{11}$$

Where:

$\underline{Q}$	lower bound of the system error covariance
$\bar{Q}$	upper bound of the system error covariance
$\underline{R}$	lower bound of the measurement error covariance
$\bar{R}$	upper bound of the measurement error covariance

A combination of all possibilities of $\underline{Q},\ \bar{Q},\ \underline{R}\ and\ \bar{R}$ (Table 1) has been evaluated and compared in such a way that a priori error covariance matrix P_k and a posteriori error covariance matrix P_{k-1} don't lose symmetry and achieve positive definite status. By keeping both P_k and P_{k-1} positive definite the Interval Probability EKF can perform better and become robust to the different noises added by the system states and the measurements error covariances. The impact of the variations of Q and R on the P_k and P_{k-1} is applied to the proposed multi-sensor fusion security monitoring system that was discussed previously in [19] where a Hyper-Fuzzy EKF was developed and investigated to enhance the capabilities of the normal EKF to handle more uncertainty and randomness of the errors obtained from the system and the sensors [19].

The measurement error covariance R have two noises which are r and θ that represent the distance and the angle variances of each sensor as in Equation (12).

$$R = \begin{bmatrix} r_{var} & 0 \\ 0 & \theta_{var} \end{bmatrix} \tag{12}$$

Whereas, Q is the process noise matrix that is diagonal to correspond with the system states as shown in Equation (13).

$$Q = \begin{bmatrix} q_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & q_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & q_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & q_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & q_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & q_6 \end{bmatrix} \tag{13}$$

Combination Number	System Error Covariance	Measurements Error Covariance
1	$\underline{Q}$	$\underline{R}$
2	$\underline{Q}$	$\bar{R}$
3	$\bar{Q}$	$\bar{R}$
4	$\bar{Q}$	$\underline{R}$

Table 1: Tested combinations of R and Q covariances

Equation (12) explains the system dynamic model that contain the position, velocity and acceleration on x-axis and y-axis of the moving agents. [19].

$$\begin{bmatrix} \tilde{x}_k(1) \\ \tilde{x}_k(2) \\ \tilde{x}_k(3) \\ \tilde{x}_k(4) \\ \tilde{x}_k(5) \\ \tilde{x}_k(6) \end{bmatrix} = \begin{bmatrix} 1 & dt & \frac{dt^2}{2} & 0 & 0 & 0 \\ 0 & 1 & dt & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & dt & \frac{dt^2}{2} \\ 0 & 0 & 0 & 0 & 1 & dt \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} s_{k-1}^x \\ v_{k-1}^x \\ a_{k-1}^x \\ s_{k-1}^y \\ v_{k-1}^y \\ a_{k-1}^y \end{bmatrix} + \mathrm{B}u_{k-1} + \omega_{k-1} \qquad (14)$$

Where:
s_k is the position of the tracked agent.
v_k is the velocity of the tracked agent.
a_k is the acceleration of the tracked agent.

The diagonal elements of the error covariances matrix P_k are the variances of the system states with themselves as they are listed in Table 2.

	$\mathbf{P_{s^x}}$	$\mathbf{P_{v^x}}$	$\mathbf{P_{a^x}}$	$\mathbf{P_{s^y}}$	$\mathbf{P_{v^y}}$	$\mathbf{P_{a^y}}$
$\mathbf{P_{s^x}}$	$P_{(s^x,s^x)}$	$P_{(s^x,v^x)}$	$P_{(s^x,a^x)}$	$P_{(s^x,s^y)}$	$P_{(s^x,v^y)}$	$P_{(s^x,a^y)}$
$\mathbf{P_{v^x}}$	$P_{(v^x,s^x)}$	$P_{(v^x,v^x)}$	$P_{(v^x,a^x)}$	$P_{(v^x,s^y)}$	$P_{(v^x,v^y)}$	$P_{(v^x,a^y)}$
$\mathbf{P_{a^x}}$	$P_{(a^x,s^x)}$	$P_{(a^x,v^x)}$	$P_{(a^x,a^x)}$	$P_{(a^x,s^y)}$	$P_{(a^x,v^y)}$	$P_{(a^x,a^y)}$
$\mathbf{P_{s^y}}$	$P_{(s^y,s^x)}$	$P_{(s^y,v^x)}$	$P_{(s^y,a^x)}$	$P_{(s^y,s^y)}$	$P_{(s^y,v^y)}$	$P_{(s^y,a^y)}$
$\mathbf{P_{v^y}}$	$P_{(v^y,s^x)}$	$P_{(v^y,v^x)}$	$P_{(v^y,a^x)}$	$P_{(v^y,s^y)}$	$P_{(v^x,v^y)}$	$P_{(v^y,a^y)}$
$\mathbf{P_{a^y}}$	$P_{(a^y,s^x)}$	$P_{(a^y,v^x)}$	$P_{(a^y,a^x)}$	$P_{(a^y,s^y)}$	$P_{(a^y,v^y)}$	$P_{(a^y,a^y)}$

Table 2: Error covariance $P_k$elements variances

For each combination of the probability interval errors R and Q (Figure 2), the error covariance matrix P_k is observed in such way that the best combination can hold this matrix symmetrically and achieve positive-definite elements as the IP EKF iterates. Those results are plotted for comparison purposes for the same moving agent track that was created by Matlab (Figure 3).

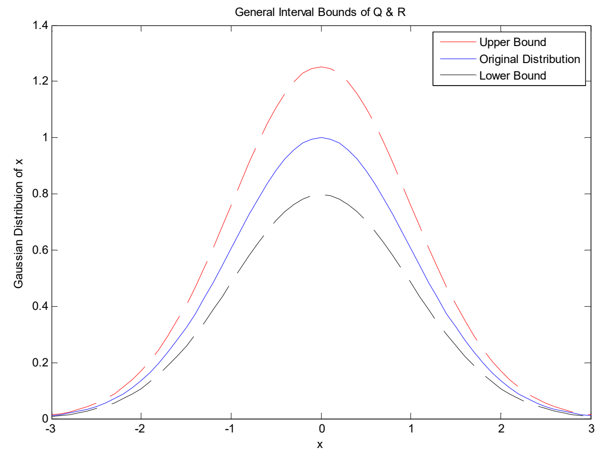

Figure. 2: Upper and Lower bounds of IP of Q and R.

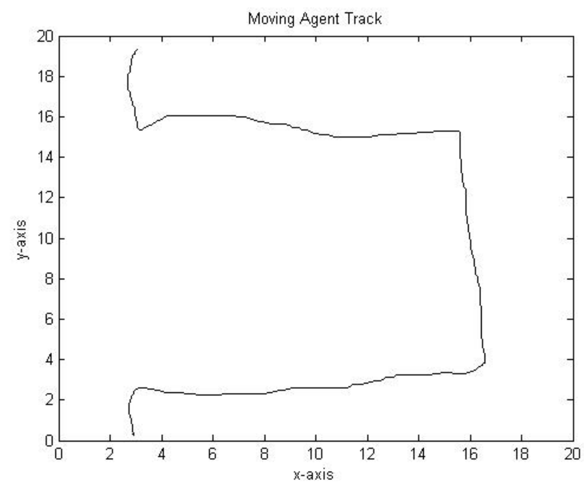

Figure. 3: Moving agent track created for testing the GIP.

Combination 1: $\underline{Q}$ (Lower) and $\underline{R}$ (Lower) bounds

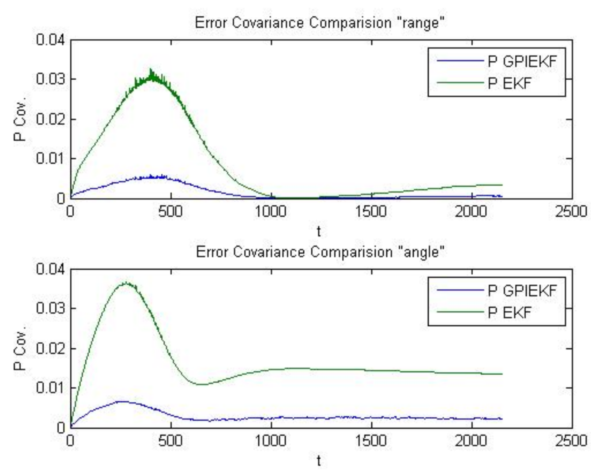

Figure. 4: Error covariance matrix P with $\underline{Q}$ & $\underline{R}$

Combination 2: $\underline{Q}$ (Lower) and $\bar{R}$ (Upper) bounds

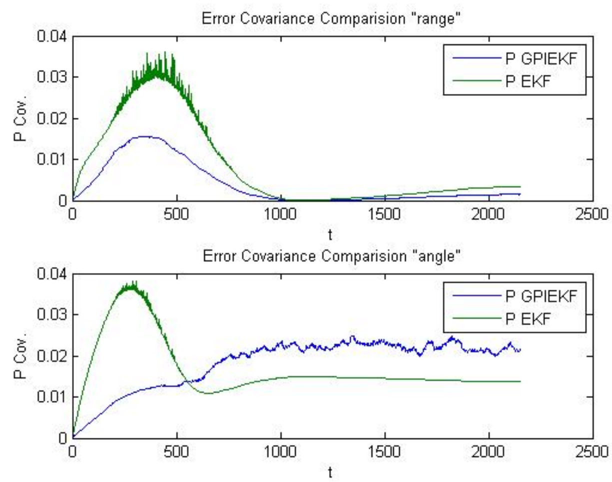

Figure. 5: Error covariance matrix P with $\underline{Q}$ & $\bar{R}$.

Combination 3: $\bar{Q}$ (Upper) and $\bar{R}$ (Upper) bounds

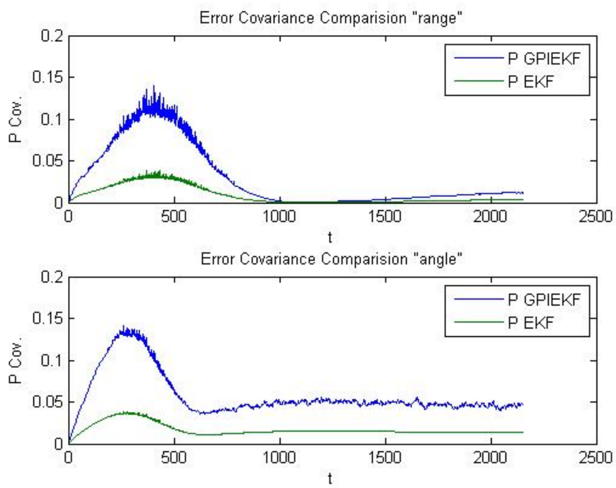

Figure. 6: Error covariance matrix P with $\bar{Q}$ & $\bar{R}$.

Combination 4: $\bar{Q}$ (Upper) and $\underline{R}$ (Lower) bounds

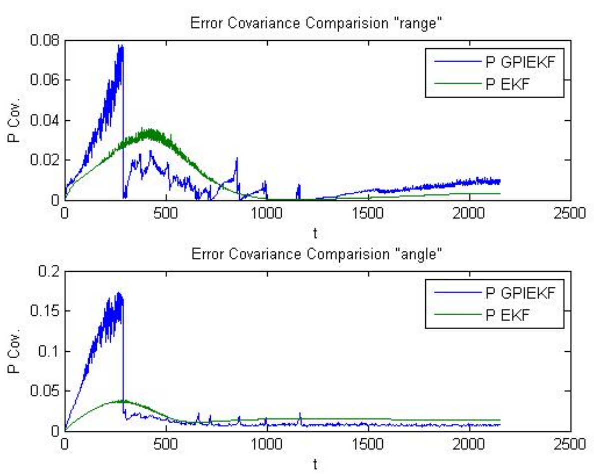

Figure. 7: Error covariance matrix P with $\bar{Q}$ & $\underline{R}$

8. Fuzzy Logic I Rules Pruning

In 1965, Dr. Lotfi Zadeh introduced Fuzzy Logic I Theory and it was presented to compute and handle data with uncertainties to mimic the human being way of making decisions [19]. FL I is able to deal with inaccurate data by applying logical reasoning and make decision based on reasoning even if the data are insufficient [19]. Fuzzy Logic consists of fuzzy sets that have smooth boundaries. The fuzzy sets have a universe of discourse (X) which is presents a linear relationship between the membership function $\mu(x)$ and the x-axis [5]. The membership function $\mu(x)$values ranges between 0 and 1 which cover the discourse elements. Fuzzy set can be presented as:

$$A = \{x, \mu_A(x) | x \in X\} \quad (15)$$

Where A is the fuzzy set, $\mu_A(x)$ is the degree of x in the fuzzy set, and X is the universe of discourse.

Fuzzy logic systems are often used in the applications that require interpretable outputs, and also applications with high level of human interaction like decision making [13]. The advantages of Fuzzy systems are that they provide a simple interaction of the domain expert with the system's designer, and they are also capable of representing the existing uncertainties of human knowledge through linguistic variables [16]. This paper will address the Fuzzy Logic type 1 reduction rules, methods, and their applications in security monitoring systems to decision-making rules.

The sensory fusion approach is a fuzzy reduction method that entails combining sensor signals before using them as input to the Fuzzy Logic Controller (FLC). Using sensory fusion, the reduction will have a lower bound if the variable could be fused. It is also clear that all variables cannot be joined trivially. Each combination has to be explained and reasoned. In practice, variables that are fused include the change of error and the error. The fundamental concepts of the variable structure system are used to determine the change of error fusion and the proposed error. Then the FLC is interpreted as VSS recognizing mode control. For a 2nd order system, the generalized error is obtained from an error signal and its derivative fusion. Therefore, a simpler first order stabilization problem results in S [15].

Hierarchical Structures and Fusion is a reduction technique that was introduced by Raju et al. in these structures the number of rules will increase linearly proportional to the number n of system variables. It is essential but difficult to decide where the variable will be placed in into the hierarchy and it is mostly based on the sensitivity and knowledge of the system analysis. In practice, all variables are categorized according to their importance [15].

A simple rule base reduction algorithm is a reduction technique based on the importance Index. This method is very effective and flexible, particularly for higher order systems. The Importance Index measures the importance of the technique to the controller. The Importance Index is defined as:

$$I_i = \sum_{j=1}^{n} \beta_i^j \quad (16)$$

When given a controllable cell to control, the rule's contribution to the final crisp controller output is weighted. Then the rule base size is reduced after Incremental Best Estimate Directed Search (IBEDS) converges on the generic rule base [17].

Reduction methods can be applied to a security monitoring system for decision-making rules. Security monitoring control designers can use reduction methods when dealing with a multivariable system. It is essential to reduce the FLC complexity to enhance its synthesis using hierarchy and fusion [18].

Fuzzy techniques can also be used in security monitoring system by using Intrusion Detection Systems (IDS). The Intrusion Detection technology can bring enhanced and flexible detection capability. Intrusion Detection System is a sophisticated decision-making process that involves factors regarding the monitored system. Therefore, fuzzy logic can be applied to reduce false positive of Intrusion Detection Systems [14].

9. Results and Discussion

Heterogenous sensors fusion for a security monitoring system has proven it is superiority over the single sensor system. By combining all data, the tracking accuracy of moving agents of the area under surveillance, the system was able to accurately minimize the measurement errors that were acquired by each single sensor.

The addition of Interval Probability lower and upper bounds for the system and measurement error covariances Q and R to the Extended Kalman Filter has added more controllability and precision to the sensor fusion, allowing the EKF to find the best combination of both error covariances within the bounds of Q and R.

After increasing the uncertainty of the states and the sensors measurements, the 1st and 2nd combinations of Interval Probability of Q and R have shown more stable IPEKF measurement estimation compared to the EKF with no IP.

In all combinations, the estimation of standard EKF diverge after few iterations; however, the IPEKF was able to diverge to the correct estimation in all combinations.

For the 3rd and 4th IP combinations, the IPEKF performance was imprecise which helped to find what Q and R lower and upper bounds combinations that made the estimation not steady.

If IPEKF is compared to the previously presented sensor fusion techniques, namely measurement fusion (MF) and state vector fusion (SVF), that were applied in [19] we can conclude that both techniques can enhance the EKF with more uncertainties presented in the system. IPEKF can be executed faster since the computation is shorter than MF-SVF method. IPEKF and MF-SVF techniques need to be investigated more with different type of applications, and sensors to understand how they differ in improving the EKF. With fine tuning of IPEKF parameters, EKF can estimate the states more accurately than the standard Extended Kalman Filter.

Applying the important index to filter the fuzzy rules of Type I fuzzy logic decision system that was introduced in [19] reduced the total number of rules which offers a less complex system that can minimize false positive of intrusion detection system.

10. Conclusion

This paper presents an extension of a previous work, namely Hyper-Fuzzy Logic Extended Kalman Filter, applying the same heterogenous sensors, Sensor Fusion techniques and Fuzzy Logic Decision to a security monitoring system. The proposed system utilizes the Interval Probability Theory to expand the range of states and sensors error covariances.

Multi-sensor fusion is very significant and has wide range of applications in indoor security and tracking activities in homes and offices.

The interval probability approach provides an avenue of evaluating the uncertainty in most mechanical systems through the minimization of the measurement error covariance and state or system error covariance. This research defines the various ways in which the Extended Kalman filter could be improved by interval probability and the impact of the variation

Pruning methods can be applied to a security monitoring system for decision-making rules. Security monitoring control designers can use reduction methods when dealing with a multivariable system. It is essential to reduce the FLC complexity to enhance its synthesis using hierarchy and fusion.

11. References

[1] Khaleghi, Bahador et al. "Multisensor Data Fusion: A Review of The State-Of-The-Art". Information Fusion, vol 14, no. 1, 2013, pp. 28-44. Elsevier BV.

[2] Luo, Ren C., and Chih-Chia Chang. "Multisensor Fusion and Integration: A Review on Approaches and Its Applications in Mechatronics". IEEE Transactions on Industrial Informatics, Vol. 8, no. 1, 2012, pp. 49-60. Institute of Electrical and Electronics Engineers (IEEE).

[3] Luo, Ren C., and Chun Chi Lai. "Multisensor Fusion-Based Concurrent Environment Mapping and Moving Object Detection for Intelligent Service Robotics". IEEE Transactions on Industrial Electronics, Vol. 61, no. 8, 2014, pp. 4043-4051. Institute of Electrical and Electronics Engineers (IEEE).

[4] T. K. Dakhlallah, M. A. Zohdy, O. M. Salim "Type-2 Fuzzy Kalman Hybrid Application for Dynamic Security Monitoring Systems based on Multiple Sensor Fusion", International Journal on Smart Sensing and Intelligent Systems, Vol.4, No.4, pp. 607-629, 2011.

[5] O. M. Salim, M. A. Zohdy and H. S. Abdel-Aty-Zohdy, "Applications of hyper-fuzzy modeling and control for bio-inspired systems", 53rd IEEE International Midwest Symposium on Circuits and Systems, Seattle, WA, pp. 169-172, 2010.

[6] Lundquist, Christian. "Sensor Fusion for Automotive Applications," Linköping University. Linköping, Sweden: LiU-Tryck, Dissertation No. 1409. Year 2011. ISBN 978-91-7393-023-9.

[7] Higham, Nicholas J. "Computing a nearest symmetric positive semidefinite matrix." Linear algebra and its applications 103 (1988): 103-118.

[8] Hu J, Wang Y, Cheng A, Zhong Z. An Extended Kalman Filtering Mechanism Based on Generalized Interval Probability. ASME. ASME J. Risk Uncertainty Part B. 2015;1(3):031002-031002-11. doi:10.1115/1.4030465.

[9] Wang, Yan. "Generalized fokker–planck equation with generalized interval probability." Mechanical Systems and Signal Processing vol.37 no.1 (2013): 92-104.

[10] Weichselberger, Kurt. "The theory of interval-probability as a unifying concept for uncertainty." International Journal of Approximate Reasoning vol.24 no.2-3 (2000): 149-170.

[11] Xie, Fengyun, Bo Wu, Youmin Hu, Yan Wang, Guangfei Jia, and Yao Cheng. "A generalized interval probability-based optimization method for training generalized hidden Markov model." Signal Processing vol.94 (2014): 319-329.

[12] Zohdy, M. A., Aftab Ali Khan, and Paul Benedict. "Fused multi-sensor data using a Kalman filter modified with interval probability support." American Control Conference, Proceedings of the 1995. Vol. 5. IEEE, 1995: 3046-3049.

[13] Chen, Min-You, and Derek A. Linkens. "Rule-base self-generation and simplification for data-driven fuzzy models." Fuzzy Systems, 2001. The 10th IEEE International Conference on. Vol. 1. IEEE, (2001); 244-260.

[14] Cheung, Yiu-ming, Yue Hao, Licheng Jiao, Yong-Chang Jiao, Jiming Liu, Jianfeng Ma, Yuping Wang, and Hujun Yin. Computational Intelligence and Security (vol. # 3802): International Conference, Cis 2005, Xi'an, China, December 15-19, 2005, Proceedings, Part Ii. Berlin Heidelberg: Springer-Verlag, 2005. Internet resource

[15] Lacrose, Veronique, and Andre Titli. "Fusion and hierarchy can help fuzzy logic controller designers." Fuzzy Systems, 199, Proceedings of the Sixth IEEE International Conference on. Vol. 2. IEEE, (1997): 1159-1165

[16] Mosam Patel. "Various Rule Pruning Techniques and Accuracy measures for Fuzzy rules." International Journal of Application or Innovation in Engineering & Management (IJAIEM), Volume 2, Issue 12, (December 2013): pp 175-178

[17] Song, Fuijun, and Samuel M. Smith. "A simple weight based fuzzy logic controller rule base reduction method." Systems, Man, and Cybernetics, 2000 IEEE International Conference on. Vol. 5. IEEE, (2000): 3794-3799

[18] Zolghadri Jahromi and Taheri. "A proposed method for learning rule weights in fuzzy rule-based classification systems." Department of Computer Science and Engineering, Shiraz University, Shiraz, Iran, (2007): 449-459

[19] Alqudaihi, Ali, Zohdy, Mohamed, Abdel-Aty-Zohdy, Hoda. "Applying Hyper-Fuzzy Extended Kalman Filter to Indoor Security Monitoring." Automatic Control and System Engineering ACSE, vol. 17, no. 1, May 2017, pp. 41–51.

Biographies

Ali A. Alqudaihi was born in Dhahran, Saudi Arabia in 1983. He received his B. Sc. degree in Electrical Engineering from Saginaw Valley State University, Saginaw, Michigan in 2009. He received his M. Sc. degree in Electrical Engineering from Oakland University, Rochester Hills, Michigan in 2011. He is currently a Ph. D. student in Electrical Engineering at Oakland University, Rochester Hills, Michigan. His research interests are in the areas of security and monitoring systems, robotics, nonlinear control, nonlinear estimation and prediction, fuzzy logic and decision making.

Mohamed A. Zohdy was born in Caro, Egypt. He received B.Sc. degree in Electrical Engineering, Cairo University, Egypt in 1968 and he received his M. Sc. and Ph. D. degrees in Electrical Engineering from University of Waterloo, Canada in 1974, and 1977 respectively. He worked in various industries: dowty, iron and steel, and spar. He is currently a Professor at Oakland University, Rochester Hills, Michigan, U.S.A. His research interests are in areas of control, estimation, communication, neural networks, fuzzy logic and hybrid systems.

Hoda S. Abdel-Aty-Zohdy was born in Cairo, Egypt. She received B. Sc. degree (with Frist Class Honors), in Electrical Engineering, Cairo University, Egypt and she received her M. Sc. and Ph. D. degrees from University of Waterloo, Ontario, Canada, all in Electrical Engineering. She has founded the Microelectronics System Design Laboratory at Oakland University. She is currently a Professor at Oakland University, Rochester Hills, Michigan, U.S.A. Her research interests are in the areas of intelligent information processing, embedded Neural Networks, Genetic Algorithms, Analog ICs, Electronic Nose and Microelectronics. Dr. Abdel-Aty-Zohdy is a senior member for the Society of Women Engineers.